Feature Importance with Deep Echo State Models for Long-Term Climate Forecasting

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Introduction

Long term forecasting Recent work has proposed the use of deep ensemble echo-state network (D-EESN) models for long term forecasting with spatio-temporal data [1][2]. D-EESN models are more computationally efficient than other current statistical methods for spatio-temporal forecasting. D-EESN models use reservoir computing, where parameters are fixed or sampled from a random distribution instead of estimated.

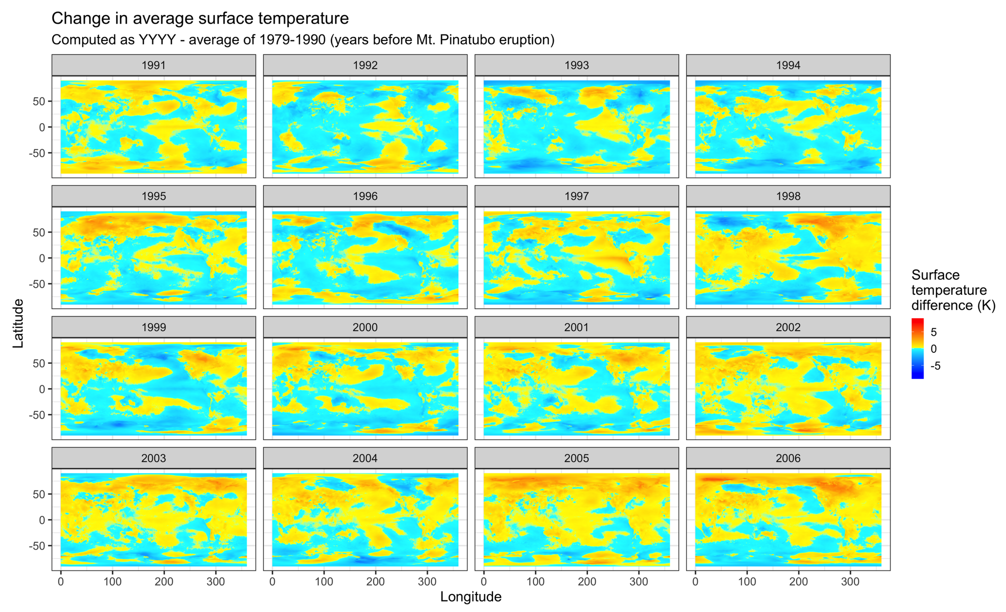
Disadvantage D-EESN models possess a common disadvantage of machine learning models: model parameters are not interpretable in the context of the application.

Explanability We are interested in developing "explainability" methods to understand the relationships in the data used by D-EESN models for prediction.

Climate Application

Climate Security Motivation Climate change is considered a serious national and global threat and measures such as solar climate interventions are becoming a real possibility. The development of algorithmic methods for understanding the impact of such events on climate change will help to inform decision makers.

Mount Pinatubo 1991 eruption of Mount Pinatubo used as an example climate event to develop algorithmic approaches for characterizing climate impacts. Figure below shows impact of eruption on surface temperature leading to a decrease for several years after eruption (ERA5 reanalysis data [3]).



Background

Permutation feature importance (PFI) **PFI for** X_j is average change in model performance when X_j is randomly permuted:

$$\mathcal{I}_j = m - \frac{1}{K}\sum_{k=1}^{K} m_{j,k}$$

where m is model performance on observed data and $m_{j,k}$ is model performance when X_j is randomly permuted for repetition $k \in \{1, ..., K\}$

(Quadratic) Echo State Network Single layer version of D-EESN model for a spatio-temporal data $\mathbf{Z}_t$ (only $\mathbf{V}_1$ and $\mathbf{V}_2$ are estimated):

$$\begin{aligned}
&\text{Data stage:} && \mathbf{Z}_t \approx \mathbf{\Phi}\boldsymbol{\alpha}_t \text{ (empirical orthogonal function decomposition)}\\
&\text{Output stage:} && \boldsymbol{\alpha}_t = \mathbf{V}_1\mathbf{h}_t + \mathbf{V}_2\mathbf{h}_t^2 + \boldsymbol{\epsilon}_t; \boldsymbol{\epsilon}_t \sim Gaussian(\mathbf{0}, \sigma_\epsilon^2\mathbf{I})\\
&\text{Hidden stage:} && \mathbf{h}_t = g_h\left(\frac{\nu}{|\lambda_w|}\mathbf{W}\mathbf{h}_{t-1} + \mathbf{U}\tilde{\mathbf{x}}_t\right)
\end{aligned}$$

where $\tilde{\mathbf{x}}_t = \left[\mathbf{x}_t', \mathbf{x}_{t-\tau^*}', ..., \mathbf{x}_{t-m\tau^*}'\right]'$ is the embedding vector (τ^* is embedding vector lag and m embedding vector length) and

$$\begin{aligned}
\mathbf{W} &= [w_{i,l}]_{i,l} : w_{i,l} = \gamma_{i,l}^{w} Unif(-a_w, a_w) + (1-\gamma_{i,l}^{w})\delta_0\\
\mathbf{U} &= [u_{i,j}]_{i,j} : u_{i,j} = \gamma_{i,j}^{u} Unif(-a_u, a_u) + (1-\gamma_{i,j}^{u})\delta_0\\
\gamma_{i,l}^{w} &\sim Bern(\pi_w); \gamma_{i,j}^{u} \sim Bern(\pi_u)
\end{aligned}$$

Feature Importance with ESN

Objective Determine importance of time t on forecast at time $t + c$ ($c > 0$)

Current implementation Apply concept of PFI by permuting input observations at time t and comparing model performance for forecasts at time $t + c$

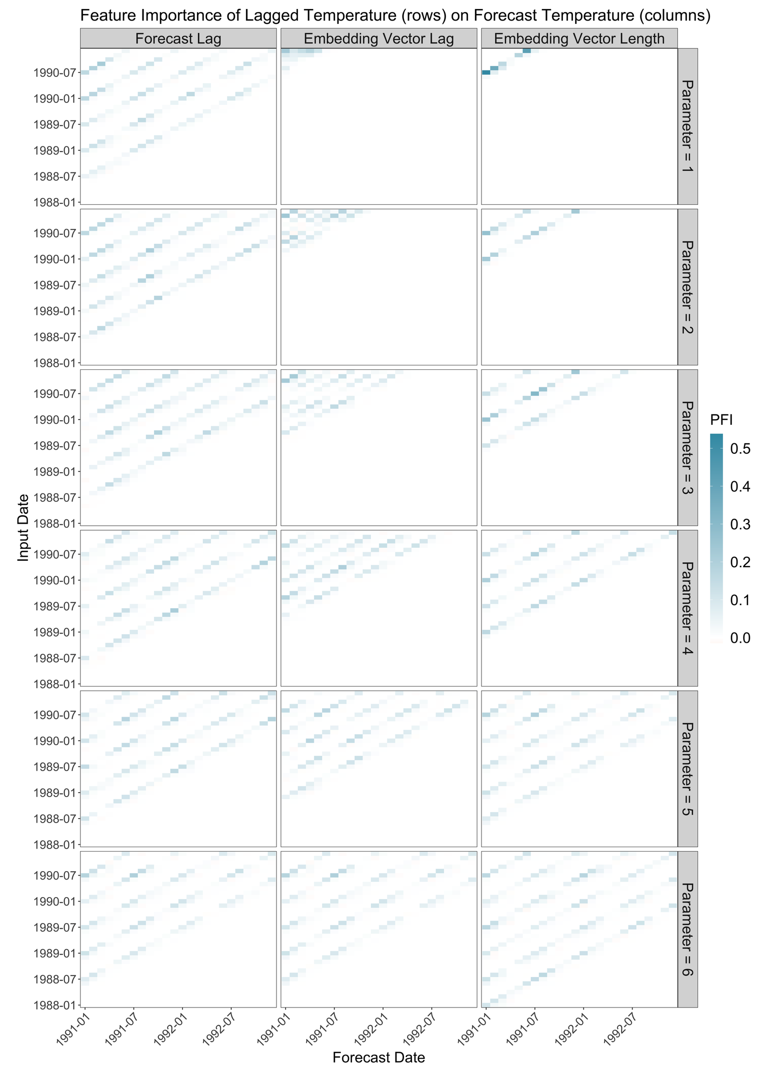
Models

- Quadratic echo state network for initial development
- Response Variable: Temperature at given pressue level
- Predictor Variables: Lagged temperatures at given pressure level
- Training Data: Monthly observations in 1979-1990
- Testing Data: Monthly observations in 1991-1992
- Preprocessing: For a given pressure level, let $y_{loc,year,month}$ be temperature at a spatial location, year, and month:
  - None: $y_{loc,year,month}$
  - Centered: $y_{loc,year,month} - \bar{y}_{loc}$ where $\bar{y}_{loc}$ is average temperature at a spatial location over all times (years and months)
  - Climatology: $y_{loc,year,month} - \bar{y}_{loc,month}$ where $\bar{y}_{loc,month}$ is average temperature at a spatial location and month over all years

Preliminary Results

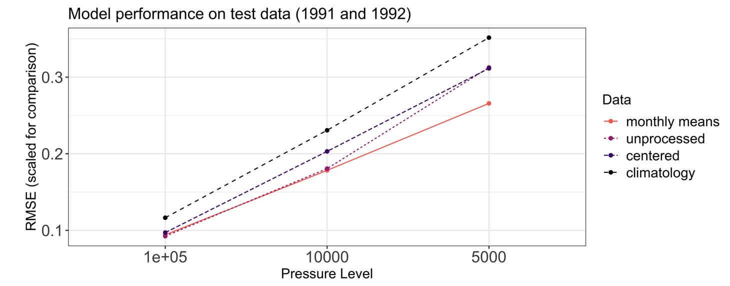
Impact of Model Tuning Parameters

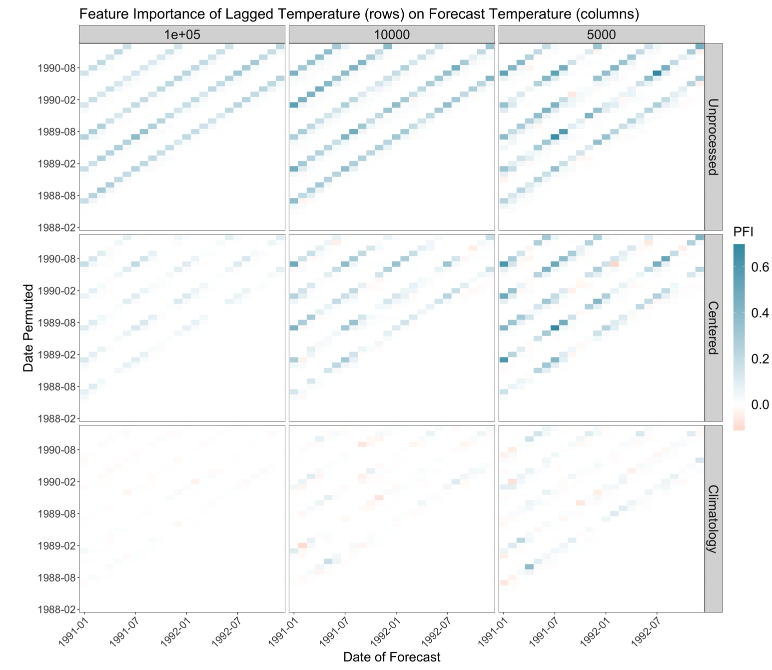
- Preprocessing: Centered
- Pressure Levels: 100,000 Pa
- Key result: Feature importance dependent on embedding vector lag and length but not forecast lag



Impact of Data Preprocessing Methods

- Preprocessing: None, centered, and climatology
- Pressure Levels: 5,000, 10,000, and 100,000 Pa
- Key results: Climatologies have worst predictive performance; seasonal pattern appears in centered PFI values; climatologies have smallest PFI values



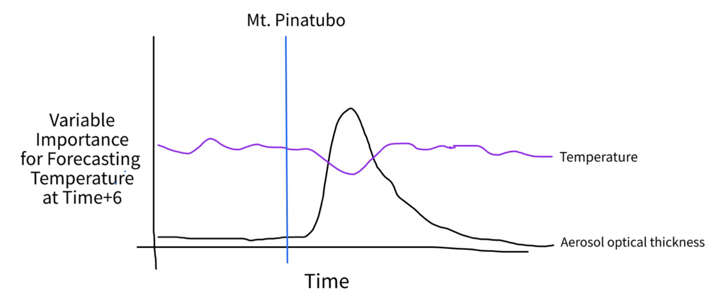


Discussion

Take Away PFI results help to understand how ESN makes use of historical temperatures

Future Steps

- Account for correlation between variables in feature importance calculation
- Include other predictor variables such as aerosol optical thickness and visualize feature importance of t on $t + c$ versus t in context of Mount Pinatubo
- Assess feature importance method on synthetic data
- Consider applicabilty of method to other deep learning models that rely on reservoir computing



References

1 McDermott, P. L., and Wikle, C. K. (2017). An ensemble quadratic echo state network for non-linear spatio-temporal forecasting. Stat, 6:315–330. https://doi.org/10.1002/sta4.160.

2 McDermott, P. L. and Wikle, C. K. (2019). Deep echo state networks with uncertainty quantification for spatio-temporal forecasting. Environmetrics, 30:e2553. https://doi.org/10.1002/env.2553.

3 https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

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